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Practical Macrofinancial Stability Analysis: A Prototype Semistructural Model

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Abstract

We introduce the MESS, the MacroEconomic Stress Scenario builder, as a macroprudential modeling framework for practical application at policymaking institutions. The framework synthesizes the key insights from academic literature on financial cycles, interactions between the real economy and the financial system, and macroprudential policy. It features an explicit description of gross quantities on the financial sector's balance sheet and explicit concepts of demand and supply on the credit market. The key equations linking the real economy and the financial sector are nonlinear, making it possible to realistically examine the costs and benefits of macroprudential policy. The intended use of the model is for policymaking institutions that need a tool which is theoretically consistent, but also malleable and flexible enough to be able to fit particular features of the economy and financial sector. The framework is already in use by financial stability authorities in several countries. This paper presents the model itself, the principles on which it is built, and use cases in policymaking institutions.

1. Introduction

This paper builds on a large body of literature on both the financial sector and its interactions with the real economy, and on understanding how risk can accumulate in the financial sector with potentially severe consequences.

In recent years, many institutions have been given new powers and responsibilities to conduct macroprudential policy, making the need for effective analytical frameworks more pressing (see e.g. Aikman et al. (2013), Galati and Moessner (2011), or Milne (2010)). However, so far there has been rather limited advances in establishing practical frameworks for modeling real-financial interactions and supporting macroprudential policy analysis. Looking back, we can spot a similar story unfolding in monetary policy several decades ago: advances in our theoretical understanding of inflation targeting policies made their way into practical frameworks only gradually, with a substantial delay.

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Currently, the common practice in macroprudential analysis is to use a number of tools, models and frameworks to describe the real economy, the financial sector as whole and individual financial institutions. These elements are usually not endogenously connected, and feedback loops (if any) are secured by manual iterative procedures, with the outputs of one model being fed as inputs into other models repeatedly. See for example the macroprudential stress testing framework by the Central Bank of Ireland, CBI (2022, p. 25, Box 2). While feasible, this approach is often cumbersome and does not allow for the full utilization of general equilibrium models, including, for example, endogenous feedback or model-consistent expectations. Additionally, using these frameworks to analyze macroprudential policy interventions is problematic due to the lack of theoretical consistency necessary for such an application.

There are several model-based frameworks currently in use at macroprudential policymaking institutions that comprehensively describe the real economy, the financial sector, and their interactions. Their underlying logic varies greatly across these models. BEAST, a framework developed by the European Central Bank (see Budnik et al. (2020)), is a large-scale disaggregated model jointly representing 19 Euro Area economies and 91 systematically important banks. The key advantages of the framework are dynamic modeling of bank balance sheets (relaxing the static balance sheet assumption of regular stress tests) and dynamic feedback between the real economy and the financial sector. The key relationships in the model are, however, described by estimated behavioral equations, which render the model largely powerless to help analyze macroprudential policy interventions. The Bank of Canada uses its MFRAR (see Fique (2017)), a three-period model for top-down stress testing. The MFRAR focuses on systemic risk and liquidity issues, as well as the potential impact of deteriorating asset performance. However, there is no endogenous feedback from the financial sector to the real economy. Finally, the Bank of England developed its RAMSI model (see Burrows et al. (2012)), which has become part of the BoE's risk assessment toolkit. As in the ECB's BEAST, the main focus of RAMSI is on the largest banks, and the model dynamics are based on estimated behavioral equations rather than structural equations. However, the banks in the model do not engage in optimizing behavior, and the model also lacks feedback from the financial system to the real economy. We find that there is room for improvement in the currently used frameworks.

We present the MESS, the MacroEconomic Stress Scenario builder, as a tractable, operationalizable, and theoretically sound model-based framework that can serve as a workhorse tool for financial stability and macroprudential analysis at institutions charged with macroprudential regulation. The framework synthesizes key insights from the literature on the financial sector to provide a model blueprint that captures the most important transmission mechanisms of financial sector shocks, but is flexible enough to be applicable (with appropriate modifications) across a range of countries and to the unique features of their financial systems. The flexibility of the framework is necessary for real-world applications, as the structure of the financial sector and regulations vary across countries and over time.

MESS is a "semi-structural" model intended for practical operation and real-world policy analysis. The term "semi-structural" implies that we build on insights from theory-based research and models (including large-scale DSGEs), and distill these into a tractable, practical framework by following the theory-based equations whenever possible but deviating when necessary to fit the data. Thus, we can retain a high degree of consistency while keeping the model flexible enough to accommodate the observed data and reporting, and regulatory and other idiosyncrasies among financial systems. The MESS equations are not derived from explicit microfoundations (such as optimization problems of economic agents in DSGEs or individual behavioral rules in agent based models), and are instead designed directly, with pragmatic simplifications and modifications introduced as necessary. Drawing again a parallel with monetary policy, a similar approach has proven extremely successful in the case of the so-called Quarterly Projection Models (QPMs), which remain a workhorse tool for monetary policy analysis and forecasting at many central banks. Compared to the three modeling frameworks discussed above, MESS exhibits considerably stronger consistency with economic theory.

MESS explicitly describes the aggregated financial sector balance sheet and links it to a standard macroeconomic model, thus making the balance sheet dynamic. Both the real and financial sectors are modeled at an aggregate level, making MESS suitable for top-down stress testing exercises. However, it needs to be complemented by further tools to produce bank-level stress testing results.

The model contains stock-flow accounting formulas for assets and liabilities: the process of cumulating and de-cumulating stocks from flows is another indispensable aspect of financial stability analysis. Furthermore, all balance sheet items are tracked in gross quantities in local currency, consistent with usual accounting practices, but the model also allows for the foreign currency of denomination on both the asset and liability sides.

Crucially, MESS simultaneously describes endogenous equilibrium on the credit market and endogenous feedback between the real and financial sectors. Several key equations describe a stylized (often nonlinear and asymmetric) behavior of financial sector variables in response to developments in the real economy, inspired by observations of these interactions in normal versus stressed times. The real economy is, in turn, affected by the balance sheet conditions of the financial system. Therefore, MESS describes the financial system and the real economy, as well as their two-way interactions within one simultaneous system.

The modeling of the financial system focuses intentionally on the medium-term dynamic solvency-related dimensions of macrofinancial stability. This is not to say that other dimensions, such as interconnectedness and liquidity issues, are of lesser importance. They simply operate at different time frequencies or are geared towards analysis of liquidity-oriented macroprudential issues and policies. Additionally, MESS does not directly incorporate the effects of microprudential regulations such as net stable funding ratio, because the aggregate financial sector balance sheet is not described in sufficient detail to be able to track these measures.

Nevertheless, the structural nature of the model allows for a stylized representation of scenarios related to liquidity constraints on operations of the financial sector. Such scenarios need to be constructed with a high degree of expert judgment, as is the case with most similar tools currently in use.

MESS is meant to be operated by the department(s) in charge of analysis and formulation of macroprudential policies, but its application usually requires coordinated effort across several departments of the policymaking institution. The financial supervision experts have superior understanding of the impact of the real economic conditions on financial system balance sheets, while experts from the monetary policy (or research) department have superior understanding of the key sources of macroeconomic volatility and how these can be captured within a macroeconomic model. It is at the intersection of these areas of expertise where the most productive work on macroprudential models takes place.

The paper proceeds as follows. Section 2 presents the most common uses of the model. Section 3 discusses the central tenets of macroprudential modeling that underpin the model presented in the paper. Section 4 presents the model itself, and Section 5 describes the implementation of macroprudential policies. Section 6 concludes.

2. Use Cases

MESS was designed with the following three principal use cases in mind:

1. Producing consistent aggregate data scenarios, including macrofinancial baseline and top-down macro stress test scenarios.
2. Performing impact and cost-benefit analysis of macroprudential policies, both through the cycle and at a point in time.
3. Simulating theoretical scenarios based on hypothetical or counterfactual assumptions.

2.1 Consistent Aggregate Data Scenarios

The semi-structural nature of MESS allows for sufficient flexibility of the model to be made consistent with the data describing the past and current conditions in the real sector and the financial system. This means the initial condition for MESS simulation corresponds to the current state of the economy. The correct initial condition is important as the nonlinear nature of the model implies that the effect of shocks varies with the initial condition. We can build a basic scenario simply by setting the proper initial condition and then simulating the model forward without any additional inputs.

Scenarios can also be conditioned on various types of inputs, of which the most relevant case is to condition the simulation on an external macroeconomic forecast, typically generated by the central banks as part of their regular monetary-policy decision making process. The resulting MESS baseline simulation is based on the initial condition and the macroeconomic forecast, and produces consistent paths of financial sector variables. Furthermore, using the delta method, described in detail in Appendix B, it is easy to impose further assumptions on top of the baseline simulation. The resulting simulation provides paths of macro and financial sector variables that are based on the initial condition and the macroeconomic forecast, but consistently deviate from the baseline simulation due to the additional assumptions.

Top-down stress tests are a natural extension of the scenario building capacity of MESS**.** A typical stress-test scenario can be built in two ways:

- Conditioning on a macroeconomic baseline and adding extra assumptions on top (such as adverse shocks to domestic or external real economic activity, or to the performance of bank assets).

- Obtaining a downside macroeconomic scenario (typically produced by the monetary policy department on demand) and using MESS to simulate the paths of financial sector variables consistent with such a scenario.

The resulting scenarios provide consistent paths of macro and financial sector variables that already take into account the key nonlinearities and feedback loops in the model, and can therefore be used to stress test individual financial institutions using standard financial supervision tools.

The stress-testing scenarios built on top of complex macroeconomic scenarios have the advantage of integrating different types of risks – credit risk, forex market risk, short-term rate market risk, etc. – unlike in simple stress-testing exercises that assume a single idiosyncratic shock, such as a simple change in the short-term market rate. In MESS all these types of risk derive consistently from the common assumptions about macroeconomic development. The importance of considering different types of risk jointly has been discussed, for example, by Drehmann et al. (2010).

Lastly, the disaggregation of the financial-system balance sheet allows us to examine and aggregate the same type of risk (e.g. credit risk) across different asset classes (e.g. loan portfolio segments).

2.2 Impact and Cost-Benefit Analysis of Macroprudential Policies

The nonlinear nature of MESS allows us to analyze the impact of a particular macroprudential policy intervention under the current and expected evolution of the economy. The baseline scenario is built by considering the current conditions in the economy (the initial condition) and the expected developments without the policy intervention (represented for example by the macroeconomic scenario generated by an external model). Next, we add the macroprudential policy intervention and obtain a second scenario where the paths of variables in the real and financial sectors have been consistently revised. Crucially, the only difference of the second scenario from the initial scenario is the effect of the macroprudential policy intervention. The scenario-based analysis of macroprudential policy costs and benefits is particularly suitable as they vary with the position in the business and financial cycle, as discussed for example by Van den Heuvel (2008).

The macroeconomic block of MESS also describes, among others, a monetary policy authority with an active monetary policy, which makes these scenarios particularly suitable for analyzing the coordination between monetary policy and macroprudential policy. This topic has been discussed in the literature for a long time but remains an open research question (see Markovic (2006) and Garcia Revelo and Levieuge (2022)).

2.3 Theoretical Simulations

MESS can be used to run theoretical, shock-minus-control simulations. These simulations are usually run from a steady-state and serve to build insight into macrofinancial interactions rather than predict the actual developments of the economy in the future. Because MESS jointly describes the real economy, the financial sector, and interactions between them, the number of simulations of possible interest is large. Typical simulations include the impact of various macroeconomic shocks on the financial sector, examination of the shocks to bank capital on the financial sector and the real economy, the impact of macroprudential policies such as the increase in capital buffers or credit caps, among others.

3. Central Tenets of Macroprudential Modeling

This section lays out several guiding principles that underpin the analysis of macrofinancial stability and the crafting of macroprudential policies. These principles permeate the model description below and translate into the key features of our modeling framework. Many of the principles are derived from the prior work of the authors developing the MAPMOD model (see Benes et al. (2014a)).

3.1 Nonlinearities

A few, but very impactful, nonlinearities are at the heart of the MESS transmission channels. While the real and the financial sectors as described in the model are nearly linear on their own, the linkages between that arise from the presence of risk (credit risk in particular) give rise to highly nonlinear behavior when economic and financial conditions deteriorate. These nonlinearities are the defining feature of the cost-benefit analysis of macroprudential policy and, in our view, attempting macroprudential policy analysis without nonlinearities makes very little sense. The importance of nonlinearities in analysis of macroprudential policy was demonstrated among others by Benes et al. (2014b) who used used MAPMOD model to examine the difference between linear and nonlinear simulations.

The interactions between the real economy and the financial sector in "normal" times can be very different under stressed conditions. It is exactly the behavior in such "unusual" times that is of interest for macroprudential policy, as it can give rise to negative feedback loops with a large, adverse impact on the economy. In contrast, linear models maintain constant responses to shocks regardless of the current state of the economy. While this is a useful and productive simplification for modeling economic behavior in "normal" times and is therefore often employed in standard macroeconomic models, it renders the model unable to describe tail events, which are a concern of macroprudential policy.

The nonlinearities also mean that the parametrization of macroprudential models cannot be achieved using conventional estimation methods. There are usually only a few short periods in the available data when the economy exhibited the "unusual" behavior that is of interest for macroprudential policy. Additionally, the behavior of the financial sector is influenced by regulations that change over time, limiting the value of information learned from past periods of financial stress for the future. This makes the task of estimating macroprudential models very challenging. In fact, the naive application of the usual estimation methods would result in significant bias and damage to the structural properties of the model, as most of the data would be generated by the economy in "normal" times, suppressing the information from "unusual" periods that is of interest. We address these issues by calibrating the model rather than estimating it, using several calibration strategies that we describe later in the Appendix.

3.2 Asymmetries

The transmission channels in MESS (and in the real world) are not only nonlinear in general, but also specifically asymmetric during the boom versus bust phases of financial cycles. This is another defining feature of the macroprudential policy trade-offs.

Asymmetry is therefore another key feature of the MESS framework. An example of asymmetry is the link between economic conditions and financial sector asset performance, such as the loan default rate. While improving economic conditions lead to declines in the portfolio default rates below its long-run levels, there is a natural autonomous level of defaults (given that even in perfect economic conditions, a certain percentage of loans will default no matter what) and therefore the space for improvement in the performance of loan books is strongly limited from below. On the other hand, adverse economic conditions can push default rates well above the equilibrium level, resulting in a disproportionately larger increase when compared to the possible improvement under favorable economic conditions.

This asymmetry creates a role for macroprudential policies, which often trade off a minor worsening of economic performance in favorable economic conditions for a lower probability of experiencing significantly adverse economic conditions.

3.3 Track of Balance Sheet Length, Not Only Net Worth

A very common approach in macro modeling is to net out the positions on individual balance sheets keeping track of each agent's (or sector's) net worth only. However, financial risk is intimately linked to the size of the balance sheets (i.e. the value of assets and liabilities), also known as the balance sheet length. The MESS modeling framework keeps track of asset and liability positions on the aggregate financial system balance sheets to properly capture the dynamic evolution of all sorts of vulnerabilities.

3.4 Stocks and Flows

Traditionally, macroeconomic models have focused on flow variables, such as GDP, inflation, interest rate, or exchange rate depreciation. Nevertheless macroprudential policy is chiefly concerned with financial sector risks, which are often embedded in outstanding stocks. The stocks might build up over extended periods of time through flows which might appear innocuous, yet when the stocks become large and suddenly unwind, the flows suddenly reverse, with severe consequences for the real economy. A typical example is a gradual buildup of credit stock in the economy, driven by moderate credit flows over a long period of time, followed by a sudden, large deleveraging when the accumulated credit stock turns out to be unsustainable. The Bank for International Settlements has produced important, policy-relevant research highlighting the importance of measuring and focusing on stocks in the financial system (see for example Borio (2013)).

MESS heeds this lesson, keeps track of stocks on the financial sector balance sheet, and maintains stock-flow consistency.

3.5 Endogenous Feedback

Endogenous feedback between the real and financial sectors of the economy is arguably the most challenging aspect of macrofinancial stability analysis, but also absolutely necessary.

In a financial crisis, the interactions between the real and financial sectors change dramatically and can devolve into a negative feedback loop. This point has been made by a number of papers, famously by Bernanke et al. (1998) or more recently by Zhang (2009). The typical negative feedback loop involves the financial sector attempting to shrink its balance sheet to deleverage, which has an adverse impact on real economic activity and, in turn, worsens the performance of assets on the financial sector balance sheet, inducing even more deleveraging. While these feedback effects can be approximated using a set of interlinked models as described in the introduction, such an approach is cumbersome and prevents a meaningful analysis of the effectiveness of macroprudential policy tools. A policy-relevant macroprudential modeling framework should describe the feedback loops endogenously.

3.6 Macroprudential Policies

A macroprudential framework should allow for positive and normative analysis of macroprudential policy tools. This can be accomplished by including a macroprudential policy instrument that implements the chosen endogenous macroprudential policy rule. Indeed, we strongly believe that macroprudential policy should be rule-based, as the danger of dynamic inconsistency in the case of discretionary policy is greater than in the case of monetary or fiscal policy.

However, we find that rule-based macroprudential policy is very difficult to operationalize in the form of a particular equation, for two principal reasons:

1. There is no consensus on a single, well-measured, reliable objective to be targeted by the endogenous macroprudential policy rule that is akin to the expected inflation deviation from target in macro models. Imposing such a rule on the model would necessarily limit its practical usefulness where there are multiple measures of risk in the financial sector. Choosing one might be problematic when the chosen measure does not indicate increased risks but other measures do, misleading the model estimation and prompting inappropriate advice for macroprudential policy.

2. There is no consensus on a main macroprudential policy tool that is akin to the nominal interest rate in macro models. An endogenous macroprudential policy would force the model to choose one tool (or a number of macroprudential policy tools with a defined hierarchy), thus reducing the ability of the model to inform policy advice and analysis in practice.

The above two points imply that an endogenous macroprudential policy rule would be highly circumstance-specific and therefore limit a models flexibility to describe a particular economy and financial system.

Another issue is the coordination of monetary and macroprudential policy, discussed for example by Haldane (2014), who argues the case in favor of coordination, or more recently by Garcia Revelo and Levieuge (2022). Yet there are important differences between the two policy areas. Unlike monetary policy, which is trying to achieve *optimal* results by smoothing the business cycle fluctuations, macroprudential policy tries to increase the *robustness* of the financial system to prevent severe downside scenarios. An explicit, endogenous policy reaction function is compatible with optimal policy, but problematic if we wish to conduct robust policy, especially in the light of the issues mentioned above. The contrast between optimal versus robust policy is an important one and macroprudential models should be built with this in mind. Our approach is to not include an endogenous macroprudential policy function but rather examine macroprudential policies as exogenous interventions in scenarios. This approach allows us to examine a wide range of macroprudential policies and study their coordination with (endogenous) monetary policy across a range of scenarios.

3.7 Heavy Reliance on Judgmental Analysis

Judgmental input is essential for any kind of model-based macroprudential analysis to become relevant. Macroprudential models therefore need to be designed with reasonable room for judgmental inputs in mind. Unobserved variables are common in macroeconomic models, but less so in traditional financial stability models. Yet they are relevant for policy. Consider, for example, a scenario in which credit-to-GDP ratio has increased by 10pp over the past three years. An important macro-prudential question is to what extent the observed movement is sustainable, an answer to which involves the use of unobserved variables and judgment. An estimation of how much of the movement has been sustainable using common statistical filters fails to incorporate an important judgmental consideration that could alter the interpretation of the current position within the financial cycle. Naive statistical filters would most likely identify a positive credit gap and signal increased financial sector risks. Indeed, if the increase in the credit-to-GDP ratio has been caused by borrowing of the same group of increasingly more indebted borrowers, this interpretation would likely be correct. However, if the increase is caused by a financial deepening where the additional credit is extended to previously unbanked borrowers, the implication is unclear. Plausibly, the financial sector risks might even decrease due to better diversification of risks.

In MESS**,** we acknowledge the limitations of quantitative methods in estimating unobserved variables, such as a sustainable level of the credit-to-GDP ratio trend, and instead treat such variables as a judgmental input into simulation. We view this approach as *in practice* superior to using quantitative methods, given that these carry their own in-built assumptions that might not be valid in a particular scenario.

4. The Model

In this section, we describe the basic model blocks and equations. We simplify the exposition by assuming that the financial system comprises a traditional banking sector only, but this assumption can easily be relaxed. Indeed, several existing implementations of MESS already use a wider definition of a financial sector and also include non-bank financial markets, such as securities markets or non-bank financial intermediaries.

4.1 Bank Balance Sheets

The stylized aggregate bank balance sheet, in its most basic form, has the following structure:

Table 1 Aggregate Bank Balance Sheets

Assets		***Liabilities***
le_t	Net loans	Non-equity funding liabilities d_t
+ $\sum l_t^k$	+ *Gross loans*	
- $\sum l_t^k$	- *Allowances for credit losses*	
ona_t	Other assets	Bank capital bk_t

All quantities on the balance sheet are tracked in gross quantities in local currency, consistent with usual accounting practices. We abstract here from local and foreign currency denomination of assets and liabilities, which will be introduced later.

The basic balance sheet is simplified by assuming that loans are the only asset on the balance sheet. Loans are indeed the largest asset class on the bank balance sheet in most countries, but the balance sheet can be expanded by incorporating other assets such as government bonds, depending on the particular features of the financial system in question.

Multi-period loan portfolio

Following the approach laid out by Benes and Lees (2008), we approximate the aggregate behavior of a portfolio consisting of a large number of multi-period loans (each with a different maturity) by a hypothetical composite loan with geometrically decreasing pay-downs and periodical interest payments. The simplifying assumption of geometrically decreasing pay-downs allows for a parameterized recursive representation and thus greatly enhances the tractability of the model dynamics. Furthermore, if needed, the entire loan portfolio can be split into a convenient number of segments with distinct characteristics, as we show later in the paper.

We now describe the time evolution of such a composite loan with no inflows of new credit after its origination; this is called a static pool in credit analysis literature. In the absence of any credit events (i.e. assuming perfect performance of the loans at all times), the composite loan has an infinite life-cycle that generates cashflows from pay-downs and interest payments:

- the pay-downs are in constant proportion to the remaining balance (hence, geometrically decreasing over time);

- the interest payments depend on the type of interest rate contract, and can either be in fixed or time-varying proportion to the remaining balance (see the lending rates later in this section).

Note that the composite loan is repaid in full only asymptotically; this is an artifact of our need for a recursive representation, and poses no conceptual or computational problems.

Table 2 Cashflows Generated by a Riskless Composite Loan

	Period 0	*Period 1*	*Period 3*	*…*
Closing book value	l_0	$(1-\theta)l_0$	$(1-\theta)^2 l_0$	…
Pay-down		θl_0	$\theta(1-\theta)l_0$	…
Interest		$rl_0 l_0$	$rl_1(1-\theta)l_0$	…
Total cashflows		$(\theta + rl\|0)l_0$		…

The lending rate, rl_t, may vary throughout the lifetime of the composite loan (except for a special case of a fixed rate contract). We express all interest rates in gross, non-annualized terms (mainly for ease of notation), so that a 4% PA rate becomes 0.01 in a quarterly model.

The pay-down parameter, $\theta \in [0, 1)$, effectively determines the average maturity of the loan portfolio. In the calibration section, we show how the parameter relates to the formal definition of Macaulay's duration, and can therefore be calibrated using the observed maturity characteristics of bank loan portfolios.

Time evolution of a dynamic pool of riskless loan portfolios

Assuming no credit events and no exchange rate valuation, a dynamic pool of loans evolves as follows:

$$l_t = (1-\theta)l_{t-1} + l_t^{\Delta}$$

where l_t^{Δ} is the amount of new loans extended at time t.

Time t cashflows (pay-down + interest) generated by the loan portfolio collected at t is equal to:

$$l_{t-1}(\theta + rl_{t-1})$$

The effective interest rate on the stock of outstanding loans (stock rate), rl_t may vary over time due to changes to interest rates on outstanding loans (floating interest rate loans are the most extreme example) but also due to the inflow of new loans which can, in general, be contracted at a rate different from the stock rate.

Credit risk and loan performance

We introduce a simplified, tractable theoretical structure for credit risk and its impact on bank balance sheets. The total value of gross loans are split into performing loans, lp_t, and nonperforming loans, ln_t:

$$l_t = lp_t + ln_t$$

Each period, the performing loans face a certain (endogenously time-varying) probability of a credit event that pushes them into default. Because we do not model individual loans but rather the entire portfolio (or portfolio segments), we use the portfolio default rate as a measure of loan performance. We denote the portfolio default rate, i.e. the proportion of the value of performing loans becoming nonperforming in a given period, by q_t.

Loans that do not experience a credit event continue to be classified as performing and continue to pay-down as described above.

Loans that do experience a credit event move into the nonperforming category and we assume they never re-perform again. The value of nonperforming loans is further split into the so called "recovery" and "write-off" buffers lnc_t and lnw_t:

$$ln_t = lnc_t + lnw_t$$

This split corresponds to the fact that a certain proportion of the remaining nonperforming value is usually still recovered, e.g. through the collateral, resale to collection agencies, etc. The recovery buffer therefore represents that part of the nonperforming loans that is recovered and continues to generate cashflows. The write-off buffer, i.e. the part of the loan that is non-recoverable, is gradually written off.

Table 3 Cashflows from Performing and Nonperforming Loans

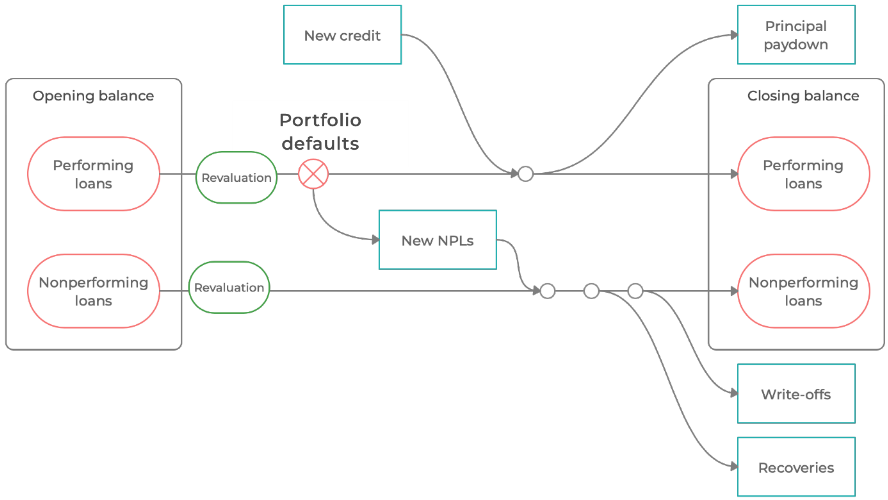
Loan performance	***Bank income***	***Flows after credit event***
Performing lp_t	Pay-down, interest	decrease by $ln_t^{\Delta} = q_t lp_t^0$
Nonperforming, recovery lnc_t	Collections, collateral, …	increase by $(1 - \lambda) ln_t^{\Delta}$
Nonperforming, write-off lnw_t	None	increase by λln_t^{Δ}

The flows in the gross loan portfolio are summarized in Table 3 where

- ln_t^{Δ} is the amount of loans that experience a credit event and become nonperforming at time *t*
- q_t is the share of performing loans experiencing a credit event (default)
- λ is parameter governing the share of the newly nonperforming loans which falls into the write-off buffer lnw

Figure 1 summarizes the stock-flow dynamics in loan portfolio with credit risk. The revaluation term in the chart represents the effect of nominal exchange rate movements on the book value of the exposure.

Figure 1 Stock-Flow Dynamics in Loan Portfolio with Credit Risk



Allowances, provisioning and write-offs

Allowances are a contra-asset (a stock variable on the asset side with a negative value) created to frontload anticipated future losses and realign (at least to some degree) the book values of an asset with its fair value. We use the term "allowances" for the stock whereas we reserve "provisions" for the incremental flow each period (an inflow into, or an outflow out of the stock of allowances).

The stock-flow logic of the allowances in the model works as follows. At the beginning of each period, the opening balance of allowances created up to that point is inherited from the previous period, a_{t-1}. The new level of allowances needed is calculated (depending on the type of allowances: backward looking or forward looking; explained later in this section), a_t; then, given the amount of write-offs, w_t, during the period, we obtain the positive or negative flow of provisions, a_t^{Δ}.

$$a_t = a_{t-1} - w_t + a_t^{\Delta}$$

Where

- w_t is period write-offs (flow)
- a_t^{Δ} is the impact of new provisions (flow) on period profit/loss

Two types of provisioning schemes can be considered in the model:

- Incurred loss (IL) based (backward-looking) allowances, ab_t
- Expected loss (EL) based (forward-looking) allowances, af_t

Depending on each country's regulations and reporting standards, different types of allowances may be needed to calculate the balance sheet (financial) capital reported on bank balance sheets, and the regulatory capital subjected to minimum requirements. Hence, the two types of provisioning schemes may actually coexist at the same time.

The IL allowances, ab_t are driven by the actual performance of the exposure. The allowances are calculated on the basis of downturn risk parameters (PD, LGD, EAD), usually proportional to the volume of the nonperforming loans and performing loans.

The conceptual definition of the EL allowances, af_t, is the difference between the present value of contractual cashflows and the present value of the expected cashflows (considering the expectations of credit events), with both of these evaluated for the current (static) pool of loans. Note that already at the loan inception, the expected cashflows are lower than contractual cashflows because we expect non-zero credit losses. For further discussion of the conceptual definition of the EL-based allowances and impact of different accounting standards, see ESRB (2019).

Portfolio segmentation

Loan portfolio segmentation is a simple, practical way of improving model accuracy in describing the bank loan portfolio. The total loan portfolio is split into *K* segments (sub-portfolios, subclasses):

$$l_t = l_t^1 + \cdots + l_t^K = \sum_{k=1}^{K} l_t^k$$

The segments differ in the following dimensions:

- risk parameters (steady-state of q and its elasticity to macro conditions, loss-given-default parameter λ, etc.)
- share of foreign exchange denomination
- average maturity, average duration of interest rate fixation, etc.

Each loan segment is tracked separately and the equations presented above exist in *K* variants that differ only in parametrization.

Since the loan portfolio segments evolve according to the same equations that only differ by parameter values, this feature greatly improves the ability of the model to describe the actual interactions between the real economy and the financial sector, while still keeping the model tractable. The key constraint here is the availability of the data to allow us to calibrate parameters for each loan segment. As an example, we can think of the total loan portfolio being segmented into mortgages, consumer credit, business credit, and other credit.

Exchange rate valuation

Exchange rate valuation effects are present whenever some parts of bank balance sheets are denominated in other than local currencies. All balance sheet quantities will be expressed (reported, tracked) in *local currency units* independently of their currency of *denomination*.

Parametrization of foreign currency denomination. For each loan segment k, we define the steady-state degree of foreign exchange denomination (exposure) by $\sigma_k \in [0, 1]$:

$$\sigma_k = \frac{l_t^{k,fcy}}{l_t^k}$$

- $\sigma_k = 0$ means fully home currency denomination
- $\sigma_k = 1$ means fully foreign currency denomination
- $0 < \sigma_k < 1$ means mixed currency denomination

The loan portfolio segment l^k is adjusted for exchange rate valuation whenever crossing a time period using the following exchange rate valuation impact indicator (depending on the parameter σ_k)

$$j_t^k = (1 - \sigma_k) + \sigma_k \frac{e_t}{e_{t-1}} = 1 + \sigma_k \left(\frac{e_t}{e_{t-1}} - 1\right)$$

Dollarization of liabilities, open net foreign positions. Part of the non-equity funding liabilities is denominated in foreign currency:

$$d_t = d_t^{lcy} + d_t^{fcy}$$

The share of liabilities denominated in foreign currency is a function of banks' net open foreign positions (expressed as a share of bank capital):

$$d_t^{fcy} = \sum_{k=1}^{K} l_t^k \cdot \sigma_k + onfx_t \cdot bk_t$$

and $onfx_t$ is an exogenous process around its steady-state value

$$onfx_t = \rho_{onfx_t} onfx_{t-1} + \left(1 - \rho_{onfx_t}\right) onfx_{ss} + \varepsilon_{onfx_t,t}.$$

4.2 Credit Risk

The credit risk is summarized by the loan default rate q_t and creates several feedback loops and linkages in the model:

- Current credit events impair loan performance: allowances, write-offs, losses, capital deterioration
- Expected credit risk is priced in new lending rates / lending conditions

- Capital adequacy stress is priced in new lending rates/conditions
- Unexpected risk (i.e. value at risk between expected risk and a particular percentile) is buffered in regulatory capital
- Macro conditions trigger credit events: there is a nonlinear mapping of current and expected macro conditions into credit events

Credit risk function

The credit risk function maps a macro conditions index (in the spirit of the Basel II/III asymptotic single risk factor approach), denoted z_t, into the actual portfolio default rate impact indicator, q_t

$$q_t = f(z_t)$$

Sign and location conventions for z_t are as follows:

- $z_t = 0$ means normal (steady-state, equilibrium) macroeconomic and macrofinancial conditions
- $z_t > 0$ means "good" times
- $z_t < 0$ means "bad" times

The macro conditions index is specific for loan segment k and combines

- current macro performance: output gap
- borrower vulnerability: annualized credit (loans) to GDP ratio
- possibly other factors related to real estate prices, exchange rate, etc.

$$z_t^k = \left(log y_t - log \overline{y}_t\right) - c_1 \left(\left[l^k / 4py \cdot y_t^{fws}\right]_t - \overline{\left[l^k / 4py \cdot y\right]_t}\right)$$

where

- y_t and $\overline{y}_t$ are output and output trend, respectively
- $\left[l^k / 4py \cdot y_t^{fws}\right]_t$ is the ratio of the credit to future expected nominal GDP
- $\overline{\left[l^k / 4py \cdot y\right]_t}$ is the sustainable (trend) credit-to-GDP ratio
- y_t^{fws} is the discounted sum of future expected GDP. The discount factor depends on the hypothetical (unobservable) level of lending rates that would cover all lending costs (to be explained later) and (expected) risks:

$$y_t^{fws} = (1 - 1/c_0)\left[y_t + 1/\left(c_0 + c_1 \hat{r}_t^{\Delta full}\right) y_{ss}^{roc}\, y_{t+1} + \cdots\right]$$

The second term in the definition of z_t^k is akin to the usual credit gap measure, which has been shown to be informative with respect to the buildup of credit risk in the financial system (see e.g. Drehmann (2013)), with two important caveats. First, we measure the debt burden with respect to the future expected income (nominal GDP) derived from model-consistent expectations, rather than the current income. The future expected income indicates the borrower's ability to service their debt in future and at the same time brings in the impact of expectations about future income (GDP growth), allowing us to simulate a range of scenarios. Second, the credit-to-GDP ratio trend is an exogenous input into simulations. As discussed above, we do not see it as plausible to reliably estimate this trend variable using quantitative methods and therefore treat it as an assumption in simulations.

The credit risk function determines both the actual performance of the existing loan portfolio and the expected credit risk used in pricing new loans. An important feature of the function is that it should be *nonlinear and asymmetric*. Empirically, in "normal" times (z_t close to 0), changes in z_t have only a small impact on q_t. With a worsening macroeconomic situation (z_t more negative), the impact on q_t increases disproportionately. As argued earlier in the paper, we view this asymmetry as a necessary feature for macroprudential models.

The functional form of the credit risk function is a generalized logistic function that is flexible and controlled by five parameters with intuitive interpretation. The credit risk function is highly dependent on the characteristics of the particular kind of credit and might vary greatly across countries and across loan segments. Calibrating the shape of this function is one of the most important, but also most challenging, parts of model development. The particular functional form we use is a generalized logistic function as in Gupta and Kundu (2010):

$$f(z_t) = q_t = \underline{q} + \left(\overline{q} - \underline{q}\right)\left[\frac{1}{1+exp-\frac{z-\mu}{\sigma}}\right]^{exp\nu}$$

Table 4 Credit Risk Function Parameters

Parameter	*Example value*	*Description*
μ	0	Location parameter: moves the curve left-right
σ	1	Scale parameter: makes the curve steeper/flatter
ν	0	Shape parameter: makes the curve asymmetric, heavy left/right
$\underline{q}$	0	Lower bound
$\overline{q}$	1	Spread between lower and upper bound

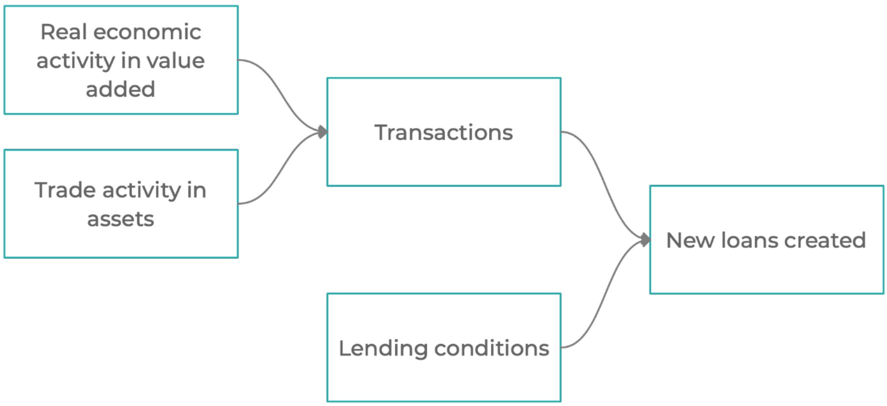
Notes: Note that the credit risk function parameters are very likely to be specific to each loan segment.

4.3 Credit Creation

Structural approach to credit creation

Motivated by insights from DSGE model literature (see Benes and Kumhof (2012) or the discussion in Werner (2012)), we take a structural approach to modeling credit creation. This approach contrasts the more common way of linking the real economic activity to the amount of newly issued credit, as depicted in Figure 2.

Figure 2 Credit Creation



The equilibrium in the credit market (Figure 2) is the result of the interaction of credit demand and credit supply. Credit supply is represented by lending conditions set by the banks through the process explained below, while credit demand comes from the need to finance transactions in the economy:

The equation that drives the production of new credit is therefore:

$$l_t^{\Delta k} = vel_t^k \cdot trn_t^k \cdot exp\varepsilon_{l\Delta,t}^k$$

where

- $l_t^{\Delta k}$ is new credit in loan segment k
- vel_t^k is the inverse velocity of new credit in segment k
- trn_t^k is the value of all the transactions that need financing to be financed by credit in segment k
- $\varepsilon_{l\Delta,t}^k$ is a shock to the new credit in segment k.

Credit demand

We start by observation that the bank deposits serve as money in the economy and therefore the volume of money increases with the total amount of credit in the economy. This observation is in contrast to the commonly cited but imprecise textbook model of the money multiplier. The credit demand can therefore also be viewed as money demand, which comes from the need to finance the current period's transactions.

Current period's transactions. Current period transactions comprise new value added (GDP: consumption, investment, etc.) and trade in existing assets

$$trn_t^k = py_t y_t + c_1^k py_t y_t^{fw}$$

The volume of trade in existing assets is proportional to the hypothetical present value of claims on future real economic activity, represented by the discounted sum of future GDP.

Inverse velocity of new credit. The equation for inverse credit velocity is an important behavioral equation that links the banks' lending conditions to the production of new credit. This part of the model is stylized and designed to provide a simple, tractable equation which still has a reasonable interpretation. We design the equation in order to stabilize the equilibrium stock of bank loans to GDP ratio and bring in the impact of lending conditions (and possibly other relevant factors):

$$\begin{aligned} vel_t^k \quad &= c_0 \cdot vel_{t-1}^k + (1 - c_0) \cdot vel_{ss}^k \\ &- c_1 \cdot \hat{r}_t^{\Delta full} \\ &+ c_2 \cdot \left([l^k/ny]_t - \overline{[l^k/ny]}_t \right) \\ &+ \varepsilon_{vel^k,t} \end{aligned}$$

where

$\hat{r}_t^{\Delta full}$ is a measure of lending conditions tightness

$\left([l^k/ny]_t - \overline{[l^k/ny]}_t \right)$ represents the current credit overhang over a sustainable level, expressed as a share of GDP; this concept is also known as the credit gap

Note there is no explicit role of macroeconomic variables such as output gap or expected GDP growth, as these are already included in the current period's transactions.

4.4 Interest Rates, Lending Conditions

Stock-flow dynamics in lending rates

Each period, banks decide on a lending rate on newly issued credit ("new lending rate") rl_t^{Δ}. The rate rl_t^{Δ} is determined by the banks based on a cost-plus loan pricing mechanism described below. The new lending rate then applies to a certain proportion, ψ_{rl}, of the stock of the pre-existing outstanding loans (i.e., these loans are repriced), and to all new loans. This is to mimic the fact that the total loan portfolio comprises loan contracts with different interest fixation periods (see Brzoza-Brzezina et al. (2014) for treatment of a similar topic within a DSGE model). The duration of interest fixation in general differs from the duration of the respective individual loans themselves. Depending on the parameter ψ_{rl}, we can choose any point between the following two limit cases to describe the average lending rate fixation period within a portfolio segment:

- $\psi_{rl} = 0$: the duration of the lending rate fixation matches exactly the duration of the underlying loan (a *fixed rate* loan) for each loan in the portfolio
- $\psi_{rl} = 1$: the lending rate is fully adjustable on the underlying loan (an *adjustable rate* loan) for each loan in the portfolio.

The effective rate that determines the interest income on the stock of outstanding loans, called the stock lending rate, rl_t, is given by

$$rl_t = rl_{t-1} + \Omega_t(rl_t^{\Delta} - rl_{t-1}) + \epsilon_{rl,t}$$

where $\Omega_t \in (0,1]$ is a (time-varying) share of new lending rates in the updated effective stock rates

$$\Omega_t = \frac{\psi_{rl}(1-\theta)lp_t^0 + l_t^{\Delta}}{lp_t}$$

and is given by the proportion of the performing loan portfolio, lp_t, to which the new rate applies, consisting of a ψ_{rl} fraction of the existing loans and all the new loans.

Lending conditions

The overall lending conditions comprise the price components (the interest rate) and non-price components. A non-price component usually takes the form of various administrative requirements such as the need to document a certain level of income, requirement for a third person to co-sign on the loan, take out life insurance policy, or similar. We represent the overall lending conditions as a shadow lending rate, which is constructed as described below. The division of the overall lending conditions into the price and non-price component will be discussed later.

We model the lending conditions (applied on loans issued in the current period or which reset their interest rate in the current period) as using the so-called "cost plus" loan pricing mechanism. The lending conditions can be split into four components:

1. Marginal funding cost (including interest rate risk) and desired margin
2. Expected borrower credit-risk premium over lending rate fixation period
3. Autonomous profit margin to cover other (non-modeled) cost drivers

4. Endogenous profit margin to cover cost of bank capital (balance sheet stress)

Short-term, base rate

The short term base rate represents the banks' desired rate of return on loans. The rate would apply to a hypothetical borrower who does not carry any credit risk whatsoever. The base rate comprises:

- the short term money market rate, rs_t, which represents the marginal cost of funding
- an autonomous profit margin, $rl_t^{\Delta apm}$

$$rl_t^{\Delta base} = rs_t + rl_t^{\Delta apm}$$

For dollarized loan segments, we take into account both LCY and FCY funding costs based on the level of dollarization:

$$rs_t = (1 - \sigma^k) rs_t^{lcy} + \sigma^k rs_t^{fcy}$$

Forward-looking rate covering credit risk

The description that follows applies for each loan segment individually. We drop the segment index k and the expectations operator for simplicity. See Duffle and Singleton (1999) for a thorough treatment of modeling the term structure of defaultable assets, which inspired our approach.

The hypothetical lending rate covering the full expected credit risk is given by

$$rl_t^{\Delta full,1} = (1 - \Psi_1)\left[\frac{1+rl_t^{\Delta base}}{1-\lambda q_{t+1}} + \psi_1 \frac{1+rl_{t+1}^{\Delta base}}{1-\lambda q_{t+2}} + \psi_2 \frac{1+rl_{t+2}^{\Delta base}}{1-\lambda q_{t+3}} + \cdots\right] + \epsilon_t^{rl\Delta full,1}$$

where

$$\Psi_1 = \left(1 - \psi_{rl,1}\right)(1 - \theta)$$

The intuition behind the equation is that to obtain the desired rate of return $rl_t^{\Delta base}$, the bank has to set the actual lending rate higher to account for the expected credit losses given by λq. In the case of a one-period loan, the lending rate would therefore be equal to (recall we express interest rates in gross terms):

$$\frac{1+rl_t^{\Delta base}}{1-\lambda q_{t+1}}$$

Furthermore, we need to account for the facts that loans are gradually repaid (governed by the inverse loan maturity parameter θ) and the lending rate can be reset before the loan matures (governed by the parameter $\psi_{rl,1}$). The term $\Psi_1$therefore discounts expected future cashflows.

Capital shortfall stress

The last component of the lending conditions reflects the possible impact of a shortfall in bank capital, or the capital shortfall stress. The variable rx_t is another shadow rate, which measures the bank capital shortfall stress. When the bank capital declines to levels that are uncomfortably close to the minimum capital requirements, the banks run increased risk that further negative shocks could push the capital below the regulatory minimum, which would trigger a regulatory action with possibly very high costs to the banks. The closer banks get to the regulatory minimum capital (measured by the distance of capital adequacy ratio CAR from the regulatory minimum), the larger is the shadow interest rate rx_t. The nonlinear function linking the CAR and the rx_t is explained in detail later. The overall shadow lending rate reflects the current and expected capital shortfall stress through the following term:

$$rl_t^{\Delta full,2} = (1 - \Psi_2)[(1 + rx_t) + \Psi_2(1 + rx_t) + \Psi_2^2(1 + rx_{t+2}) + \cdots] + \epsilon_t^{rl\Delta full,2}$$

Overall full-cost lending rate

The overall hypothetical lending rate reflecting all costs is given by

$$1 + rl_t^{\Delta full} = \left(1 + rl_t^{\Delta full,1}\right) \cdot \left(1 + rl_t^{\Delta full,2}\right)$$

Price and non-price lending conditions

It is empirically difficult to match the changes in observed lending rates to the changes in the volume of new credit as the data commonly show little volatility in lending rates. This stylized fact can only be squared with the changes observed in new credit volumes by assuming an implausibly high elasticity. We introduce non-price lending conditions in the model, alongside interest rates, as additional costs that banks impose on borrowers when they wish to tighten lending conditions. The non-price lending conditions can encompass LTV ratios, collateral requirements, requirements to obtain co-signature on the loan, etc. The literature on non-price lending conditions suggests these are empirically important (see de Bondt et al. (2010) or Strahan (1999)).

We reflect the role of non-price lending conditions by splitting the hypothetical full-cost rate $rl_t^{\Delta full}$ into

- a price component, i.e. the actually observed new lending rate;
- non-price conditions measured by an interest rate equivalent (passed on to borrowers).

The extraction of the price component is based on the spread over the base rate. Parameter $c_1$controls which share of risk is reflected in the price components as opposed to the non-price conditions:

$$rl_t^{\Delta} = rl_t^{\Delta base} + c_1\left(rl_t^{\Delta full} - rl_t^{\Delta base}\right) + (1 - c_1)\left(rl_{ss}^{\Delta full} - rl_{ss}^{\Delta base}\right)$$

The hypothetical full-cost rate $rl_t^{\Delta full}$ enters the aggregate demand and credit demand equations, as it represents the true cost of credit for borrowers.

The observed lending raterl_t^{Δ} enters the bank profits calculations.

Gap in lending conditions

The overall measure of lending conditions, the hypothetical full cost rate $rl_t^{\Delta full}$, reflects both the central bank policy setting (via the base rate) as well as additional factors reflecting banks' consideration of the credit risk, capital position, and other factors. We therefore introduce the spread of the full risk rate over the short-term money market rate as

$$sp_t^{\Delta full} = rl_t^{\Delta full} - rs_t,$$

which measures the additional lending conditions tightening / easing on top of the central bank's monetary policy actions. We stationarize this variable by subtracting its steady-state value to arrive at the gap in hypothetical full lending conditions

$$\hat{r}_t^{\Delta full} = sp_t^{\Delta full} - sp_{ss}^{\Delta full}$$

This variable enters the equations driving credit creation described above, as well as equations driving real economic activity described later.

Funding rates

The new funding rates are set as a markdown (with a parameterized autonomous profit margin, rd_t^{apm}) below the short-term money market rate (averaged across the currencies of denomination)

$$rd_t^{\Delta base} = rs_t - rd_t^{apm} + \epsilon_{rd\Delta,t}$$
$$rs_t = (1 - \sigma)rs_t^{lcy} + \sigma rs_t^{fcy}$$

The effective rate that determines the interest expense on the stock of non-equity liabilities (deposits), called the stock funding rate, rd_t, is given by

$$rd_t = rd_{t-1} + \psi_{rd}(rd_t^{\Delta} - rd_{t-1}) + \epsilon_{rd\ \ ,t}$$

where ψ_{rl} (0, 1] is the effective impact of new funding rates on the stock rates, and is parameterized as an exogenous number.

4.5 Bank Capital and Profits

Bank capital (i.e. the net worth of a bank balance sheet) is one of the key indicators of the overall health of the institution, for reasons arising from both market discipline and prudential regulation. Depending on the reporting and regulatory standards, multiple definitions of bank capital coexist and are used in different contexts: for instance, financial capital for public reporting purposes, different tiers of regulatory capital for calculating capital adequacy, etc.

Bank capital plays a significant role in the feedback channels between the financial sector and the real macroeconomy. Shortfalls in bank capital usually result in banks hiking up their lending spreads in attempts to increase profit margins, and restricting their lending conditions in attempts to deleverage. Abundance of bank capital, on the other hand, may quickly translate into credit booms with ensuing asset price inflation and real economy expansion, healthy or risky alike.

Bank capital

Bank capital can be accumulated (or decumulated) either from internal or external source. The only internal source of bank capital in MESS is retained profits. The external sources of bank capital are newly issued equity, recapitalization, dividend payouts (negative), etc.

Bank capital accumulates according to the following equation:

$$bk_t = bk_{t-1} + prof_t + xcf_t$$

- bk_t is bank capital (as recorded on the balance sheet)
- $prof_t$ is an internal flow of capital (profit or loss after dividend payouts) recorded on the closing balance of the balance sheets at $t-1$ and credit events throughout t
- xcf_t is an external flow of capital throughout t: dividends paid out (negative, outflows), new equity issuance (positive, inflow), equity withdrawals by parent companies (outflow), recapitalization flows (inflow), etc.

Internal capital flows. Period profit/loss, in the basic model version, is comprised of the following items:

- Interest income on loans (by segments)
- Income on other assets
- Other income (proxy for fees, commissions, etc.) – modeled as a proportion of newly issued credit, but could also be linked to exchange rate (commissions), etc.
- Interest expense on non-equity liabilities (by currency of denomination)
- Provisioning and write-offs
- Exchange rate valuation

External capital flows. The steady-state level of external capital flows xcf is determined such that the CAR remains equal to target CAR in equilibrium. Many model simulations related to capital-based policies are heavily affected by our assumptions as to how the xcf reacts to changes in the bank capital position (CAR).

We can move between two corner cases:

- $c_1 \to 0$ External capital flows do not respond to fluctuations in the capital adequacy ratio. Bank owners do not adjust external flows (e.g. dividends) based on the current profit/loss at all.
- $c_1 \to 1$ External capital flows bring the capital adequacy ratio to its target level at all times. Bank owners adjust external flows (e.g. cut dividends, add capital) to always ensure $car_t = car_t^{tar}$.

$$(1 - c_1)\left(\left[\frac{xcf}{bk}\right]_t - \left[\frac{xcf}{bk}\right]_{ss}\right) - c_1(car_t - car_t^{tar}) = 0$$

Capital adequacy ratio, target level of capital

Regulatory capital is introduced in case the capital as recorded on the bank balance sheet is not identical to the regulatory capital used for financial supervision purposes:

$$regk_t = \left[\frac{regk}{bk}\right]_t bk_t$$

Capital adequacy ratio is then calculated simply as

$$car_t = \frac{regk_t}{riskw_t l_t}$$

where the $riskw_t$ is the effective average risk weight, an exogenous variable.

Banks target an optimal, "comfort" level of CAR that consists of

- car_t^{min} as the regulatory minimum (including regulatory buffers)
- car_t^{exc} as the excess capital above the regulatory minimum. Banks are motivated to hold excess capital to avoid approaching the regulatory minimum in case of unexpected adverse shocks (see Peura and Keppo (2006) or Estrella (2004) for a detailed discussion).

$$car_t \to car_t^{tar}$$
$$car_t^{tar} = car_t^{min} + car_t^{exc}$$

Feedback to lending conditions

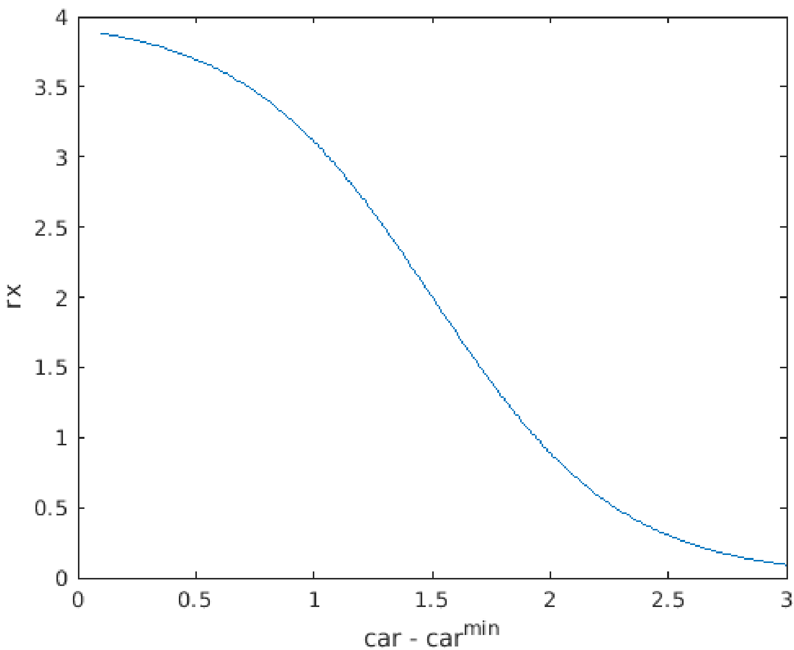
Negative shocks can push the actual CAR car_t below the optimal level car^{tar}. If car_t approaches the regulatory minimum car_t^{min}, the capital shortfall triggers an increase in the capital adequacy risk surcharge rx_t. The surcharge is added to the lending rates as the bank attempts to increase profitability as well as reduce lending to shrink its balance sheet.

- $car_t < car_t^{tar}$ Tighter lending conditions: Increase spreads, reduce leverage
- $car_t > car_t^{tar}$ Lax lending conditions: Reduce spreads, expand balance sheets.

The risk surcharge rx_t is a nonlinear function of the distance to regulatory capital shortfall (distance car_t to car_t^{min}), similar to the credit risk function. This function is the second key nonlinearity in the model. The nonlinearity implies that changes in the bank capital position (expressed in terms of the CAR) have a negligible impact on lending conditions as long as the actual CAR is sufficiently far from the target level. However, as the CAR approaches the regulatory minimum, banks react by a sharp tightening of the lending conditions with large adverse consequences for real economic activity. This nonlinearity allows the model to replicate financial crises with a sudden emergence of negative feedback loops.

Note that the function (depicted with illustrative calibration in Figure 3) is again nonlinear and asymmetrical: the improvements in the CAR yield only a marginal relaxation of the lending conditions, but a sharp decline in the CAR can trigger a sharp tightening, with negative consequences for the real economy.

Figure 3 Capital Adequacy Risk Surcharge



4.6 Macroeconomy

Real economic activity (including external macro variables) is represented by a semi-structural macro model of a QPM variety, widely used as a workhorse model for monetary policy analysis and forecasting at central banks (see Berg et al. (2006) for a basic QPM exposition). The main advantages of using a QPM style of macro module are its operational simplicity, compatibility with monetary policy frameworks, and its great flexibility and extensibility to include linkages with the financial sector. Nevertheless it is possible to replace the QPM with any macroeconomic model of a business cycle, as long as the linkages presented below can be introduced.

The dynamic core of a typical QPM includes the following set of observed variables:

- real GDP
- CPI inflation
- the short-term interest rate
- the nominal exchange rate

The behavioral dynamic equations are then built around a larger number of variables derived from these basic ones, with some of them being intrinsically unobserved. The derived variables include potential GDP, the GDP gap, the real interest rate, its trend and gap, the real exchange rate, its trend and gap, and so forth.

The extra elements we add to a plain vanilla QPM to introduce the linkages between the real macroeconomy and the financial system include (i) new mechanisms incorporated within the existing QPM equations, and (ii) new equations to define macro variables not typically found within QPMs but needed in MESS**.**

Lending conditions in aggregate demand

The aggregate demand equation is the key equation where we place the impact of the financial sector on real economic activity.

A QPM aggregate demand equation explains the dynamics of the output gap, $\hat{y}_t$, by its own lag, forward-looking expectations, the gap in the real short-term money market rate (usually a monetary policy related rate), $\widehat{ri}_t$, the gap in the real exchange rate, $\widehat{re},$ and foreign demand, $\hat{y}_t$:

$$\begin{aligned} log\hat{y}_t \quad &= c_1 log\hat{y}_{t-1} + c_2 log\hat{y} \\ &- c_3\widehat{ri} + c_4 log\widehat{re} + c_5 log\hat{y}_t^* + \epsilon_{\hat{y},t} \end{aligned}$$

The effect of the financial sector through lending conditions, $\hat{r}_t^{\Delta full}$, is put on top of the standard short-term real interest rate gap: any tightening (or easing) in lending conditions exercises an extra constraint on (or boost to) aggregate demand by making the financing of expenditures costlier and more difficult to access (or cheaper and more easily obtainable):

$$
\begin{aligned}
log\hat{y}_t &= c_1 log\hat{y}_{t-1} + c_2 log\hat{y} \\
&\quad - c_3\widehat{ri} + c_4 log\widehat{re} + c_5 log\hat{y}^*_t - c_6\hat{r}^{\Delta full}_t + \epsilon_{\hat{y},t}
\end{aligned}
$$

Hysteresis in aggregate supply

Long-run aggregate supply is introduced in QPMs as an independent trend in potential GDP, $\overline{y}_t$, defined as the level of GDP consistent with no inflation pressures arising from domestic supply-demand interactions.

$$
\Delta log\overline{y}_t = c_0\Delta log\overline{y}_{t-1} + (1-c_0)logy^{roc}_{ss} + \epsilon_{\overline{y},t}
$$

The assumed exogeneity of potential GDP is a convenience feature in monetary policy models, acknowledging that monetary policy and cyclical fluctuations usually have very little or no impact on the long-run supply-side capacity of the economy.

In macrofinancial scenarios under large distress though we may want to make potential GDP path-dependent: episodes of large and persistent slack in demand may cause long-lasting damage to the economy's supply-side capacity. Such hysteresis may also tip the balance of costs and benefits of macroprudential policy actions.

We add hysteresis to potential GDP through the cumulative effect of GDP gaps:

$$
\Delta log\overline{y}_t = c_0\Delta log\overline{y}_{t-1} + (1-c_0)logy^{roc}_{ss} + c_1 log\hat{y}_t + \epsilon_{\overline{y},t}
$$

Present value of real income

This variable captures long-term expected present values of real income (based on GDP). The present value is the basis for the fundamental value of assets used in the credit demand equation (the value of economic transactions):

$$
y^{fw}_t = (1 - 1/\delta_{ss})[y_t + \delta_t\, 1/y^{roc}_{ss}\, y_{t+1} + \cdots]
$$

where

$$
\delta_t \equiv \frac{1}{c_0 + c_1\hat{r}^{\Delta full}_t}
$$

Normalized for analytical convenience so that

$$
y^{fw}_{ss} = y_{ss}
$$

Asset prices

A common trend in the real fundamental value of assets is given by

$$
ass_t = y^{fw}_t
$$

and the nominal fundamental value of assets is therefore

$$nass_t^{fnd} = py_t \cdot y_t^{fw}$$

The actually observed market value of assets includes systematic persistent deviations of the actual value from their fundamentals, termed “bubble” here:

$$nass_t^{mkt} = nass_t^{fnd} \cdot nass_t^{bub}$$

Exchange rate and interest parity

The medium-term tendencies in the forex market are described by a parity equation between the short-term local-currency rate, rs_t^{lcy}, and the short-term foreign currency rate, rs_t^{fcy}, adjusted for expected depreciation of local currency, e_{t+1}/e_t, and an autonomous country premium, acp_t, inclusive of all factors that may give rise to a disparity in the markets such as sovereign credit risk, currency risk, liquidity factors, regional preferences of investors, etc.

$$1 + rs_t^{lcy} = \left(1 + rs_t^{fcy}\right) E_t[e_{t+1}/e_t](1 + acp_t) exp \epsilon_{e,t}$$

The country premium is most often an autonomous assumption introduced as a mechanical dynamic process not affected by other variables in the QPM. For macrofinancial scenarios, we again need to break this independence, and we insert into the forex market premium the indicator of lending conditions, $\hat{r}_t^{\Delta full}$.

However, we do not include the lending conditions on the grounds of causality. Here, we use the channel as a semi-structural shortcut to say that severely damaged lending conditions are indicative of times when other macro factors would quite likely be exerting depreciation pressures on local currency.

$$\begin{aligned} 1 + rs_t^{lcy} \quad & \left(1 + rs_t^{fcy}\right) E_t[e_{t+1}/e_t](1 + prem_t) exp \epsilon_{e,t} \\ prem_t \quad & acp_t + c_1 \hat{r}_t^{\Delta full} + \epsilon_{prem,t} \end{aligned}$$

Nominal GDP

The GDP deflator, py_t, is simply linked to the CPI in their respective rates of changes:

$$\Delta log py_t = \Delta log cpi_t + \epsilon_{py,t}$$

The nominal deflator then enables us to define nominal GDP, ny_t, used in the financial sector equations as a benchmark for the nominal value of economic activity:

$$ny_t = py_t \cdot y_t$$

4.7 International Linkages

The model integrates the following connections to the foreign sector:

- Standard macroeconomic linkages, including the influence of foreign demand on domestic demand and the impact of foreign interest rates on domestic rates, among others.
- The direct influence of foreign interest rates, denoted as rs_t^{fcy}, on bank funding costs and lending rates.

While it is possible to offer a more detailed description of the international linkages to describe the effects of global financial cycles better, doing so would considerably increase the model's complexity. Given that the primary objective of this model is to serve as a flexible tool for practical applications, we have opted not to incorporate these features. However, we are in the process of developing a multi-country DSGE model that, although less flexible and operable, will provide a more comprehensive insight into international financial spillovers, thereby complementing the model presented in this paper.

5. Macroprudential Policy in the Model

As explained in the introduction, MESS is primarily designed for medium-term solvency-centered analysis. To that end, we can incorporate a number of different types of macroprudential policies and regulations. Some of them have a very straightforward representation in the equations (such as capital adequacy measures) while some other regulations need to be conceptualized using somewhat more abstract concepts (such as the shadow price of DSTI caps).

While liquidity is not the aspect of macrofinancial stability that our model is built around (mainly because liquidity issues and regulations work along different dimensions, such as intratemporal network and interconnectedness dimensions), we also show how to incorporate the effects of liquidity regulations within the current framework.

The impact of many macroprudential tools is contingent not solely on the policy itself, but also on its announcement and communication strategy. Given that we treat all policies as exogenous shocks in our model, it is crucial to introduce these shocks as *anticipated* where appropriate. Such anticipated shocks are incorporated into the agents' information sets right from the start of the simulation, independent of the period they actually occur, thereby enabling us to describe a variety of scenarios. It is important to note that the anticipation status of a shock is not an intrinsic property of the model; instead, it is defined by the approach we adopt in solving the model, as well as in setting up specific simulations.

Capital adequacy policies

Capital adequacy policies are represented as changes in the regulatory minimum imposed on the capital adequacy ratio, car_t^{min}. We can think of car_t^{min} as the sum of the baseline (and usually fixed) *microprudential* minimum, car_t^{regmin}, and a number of different kinds of macroprudential buffers and surcharges, such as the counter-cyclical capital buffer:

$$car_t^{min} = car_t^{regmin} + car_t^{ccyb}$$

The counter-cyclical capital buffer can be represented as a simple exogenous AR(1) process:

$$car_t^{ccyb} = \rho_{ccyb} car_{t-1}^{ccyb} + \epsilon_t^{ccyb}$$

Recall that banks maintain an excess capital above the regulatory minimum to avoid the cost of unexpected regulatory capital shortfalls

$$car_t^{tar} = car_t^{min} + car_t^{exc}$$

Recall also that our preferred approach is to activate macroprudential policy instruments in simulations through exogenous shocks. By introducing a positive shock to car_t^{ccyb}, the optimal capital level car_t^{tar} shifts up and the banks find themselves with less excess capital than desired. The equilibrium car_t therefore shifts to a new, higher value and banks tighten lending conditions somewhat to build up additional capital. This banks' response is endogenous to the model via the capital adequacy risk surcharge described earlier.

When the banking sector experiences a large negative shock and its actual CAR, car_t, shifts precariously close to car_t^{min}, banks might again react by tightening the lending conditions by increasing the capital adequacy risk surcharge; however the tightening could be considerably more severe, depending on the size of the negative shock and its impact on the bank capital position. The tightening would have an adverse impact on the real economic activity, possibly worsening the bank capital position further. To prevent this, macroprudential policy can release the counter-cyclical capital buffer, car^{ccyb} so as to increase the distance $\left(car \middle| t - car_t^{min}\right)$ and put banks in a more comfortable position.

Note that the asymmetries and nonlinearities built into the model imply that when the capital buildup is implemented in "normal" times when the economy is close to equilibrium, the associated costs in terms of lost economic output are small (but nonzero). On the other hand, when the release of capital buffers occurs in a situation when the economy and financial sector are in a significantly adverse scenario, the benefits are considerably larger. The presence of nonlinearities and asymmetries is therefore key to demonstrating the benefits of macroprudential policies.

Policies affecting lender-borrower relationships

Policies that directly affect the interactions between the lender's and borrower's balance sheets typically include caps on various indicators of the borrowers' capacity to repay their obligations, such as debt service to income ratios or loan to value ratios.

We can define a new auxiliary variable x_t that measures to what extent the policy is limit binding, which is equal to the distance between the actual credit-to-GDP ratio and the limit. Then we can design a function similar to the credit risk function which maps $x_t$onto a new lending rate surcharge rp_t, which will then be added to the overall measure of lending conditions tightness , $\hat{r}_t^{\Delta full}$. When p_t approaches zero, the regulatory limits become binding and lending conditions tighten so as to prevent issuance of new credit, which also leads to a slowdown in real economic activity. The precise link between rp_t and , $\hat{r}_t^{\Delta full}$ depends on the particular nature of the regulation under consideration.

Liquidity oriented measures

Liquidity regulations include a range of constraints imposed on certain classes of assets and liabilites, such as a net stable funding ratio, or a liquidity coverage ratio (involving high-quality liquid asset criteria).

These are represented in a stylized way only, since the financial sector in our model does not (intentionally) deal with mutual exposures at the level of individual institutions, a necessary element in modeling liquidity related channels of transmissions and liquidity regulations. However, we can at least mimic these as exogenous processes and measure their distance to regulatory limits. As the actual variables approach these limits, they trigger increases in the funding cost, and feed into price and non-price lending conditions, seeping all the way to real economic activity through the channels of transmission present in our model.

6. Conclusions

There is a considerable room for practical macroprudential modeling frameworks for use in policy-making institutions. In sharp contrast to the monetary policy area, there is no commonly used and understood modeling framework that would be versatile enough to be applicable to multiple areas such as macroprudential analysis, stress-testing, and relevant simulation experiments. Moreover, the lack of a commonly understood modeling framework also implies a lack of a reference point that would aide discussions and help connect experts across different institutions and different fields of expertize (macroeconomics, financial stability, macroprudential regulation).

We strive to provide a framework that maintains a high level of aggregation and theoretical consistency but provides sufficient detail to be relevant in real-world applications. In the process, we have to navigate several trade-offs:

- *Theoretical consistency versus flexibility.*
- *High level of detail versus tractability.*
- *Nonlinearity versus numerical computability.*

This paper provides a blueprint that needs to be tailored to each economy, not only through country-specific calibration of parameters, but also through changes to equations or possible model extensions to describe the particular economy. The heterogeneity across financial systems and regulations is arguably greater than heterogeneity across real economies, which requires a greater amount of model customization.

In practical applications, the role of expert judgment is indispensable. Judgment permeates model development, calibration, but also set up of simulations. While this is true to some extent of all macroeconomic models, we argue that the amount of judgment needed in macroprudential modeling is greater than elsewhere. Expert judgment should therefore embraced and explicitly considered in any formal process that makes use of macroprudential models. The structural nature of the MESS model not only allows for expert judgment, but facilitates it because model shocks have structural interpretation, which makes the imposition of tractable expert judgment easier.

APPENDIX

Part A. Selected Equations

This appendix presents selected equations that were omitted in the main text for brevity.

Formal definition of EL-based allowances in the model. The following part is inspired by the discussion of formulas for deriving IFRS9-consistent lifetime expected credit loss by Engelmann (2020) and related work by Hlawatsch and Ostrowski (2010). Because the write-off buffer, lnw_t, has no recovery at all, the allowances can be expressed as

$$a_t = pvc_t l_t - pvx_t lp_t + lnc_t$$

where

- pvc_t is the present value (PV) of contractual cashflows of a unit sized portfolio of loans
- pvx_t is the PV of expected cashflows of a unit sized portfolio of loans.

Note that the PV of the recovery buffer of NPLs is exactly equal to its book value by assumption (see the section on Time evolution of dynamic loan portfolio with credit risk).

Present value of contractual cashflows. The present value of contractual cashflows from a static loan pool of unit size book value (dropping the expectations operator) is given by the sum of discounted expected future cashflows:

$$\begin{aligned} pvc_t &= \delta_{t,t+1}\left(\theta_{lp} + rl_t\right) \\ &\quad + \delta_{t,t+2}(1-\theta_{lp})\left(\theta_{lp} + rl_{t+1}\right) \\ &\quad + \delta_{t,t+3}(1-\theta_{lp})^2\left(\theta_{lp} + rl_{t+2}\right) \\ &\quad + \cdots \end{aligned}$$

with the discount factors given by

$$\begin{aligned} \delta_{t,t+1} &= \frac{1}{1+rl_t} \\ \delta_{t,t+2} &= \delta_{t,t+1}\delta_{t+1,t+2} = \frac{1}{(1+rl_t)(1+rl_{t+1})} \\ &\cdots \end{aligned}$$

This can be expressed by a recursive formula

$$pvc_t = \delta_{t,t+1}\left[\left(\theta_{lp} + rl_t\right) + \left(1-\theta_{lp}\right)pvc_{t+1}\right]$$

It is easy to show that $pvc_t = 1$.

Present value of expected cashflows. The present value of expected cashflows from a static pool of unit size (dropping the expectations operator) takes into account also the probability and impact of credit events:

$$
\begin{aligned}
pvx_t \quad &= \delta^{**}_{t,t+1}\big(\theta_{lp} + rl_t\big) + \ \delta^{**}_{t,t+2}(1-\theta_{lp})\big(\theta_{lp} + rl_{t+1}\big)\cdots \\
&+ (1-\lambda)q_{t+1}\cdot 1 + \delta^{**}_{t,t+1}(1-\lambda)q_{t+2}\cdot 1 + \cdots
\end{aligned}
$$

where the first row is the present value of cashflows associated with the performing part of the loan portfolio whereas the second row is the present value to be recovered on the nonperforming part of the portfolio (turning nonperforming at the beginning of period $t+1$, period$t+2$, etc.)

The discount factors used in the pvx_t calculations are given by

$$
\delta^{**}_{t,t+1} = \frac{1-q_{t+1}}{1+rl_t}, \quad \delta^{**}_{t,t+1} = \delta^{**}_{t,t+2}\delta^{**}_{t+1,t+2} = \frac{(1-q_{t+1})(1-q_{t+2})}{(1+rl_t)(1+rl_{t+1})}, \quad etc.
$$

This can be expressed by a recursive formula

$$
pvx_t = \delta^{**}_{t,t+1}\big[\theta_{lp} + rl_t + \big(1-\theta_{lp}\big)pvx_{t+1}\big] + (1-\lambda)q_{t+1}
$$

It is easy to show that $pvx_t < 1$ as long as $\lambda q_t > 0$.

Steady-state present value of expected cashflows

Along a steady-state path, even if loan volumes are growing, the present value of expected cashflows from a unit portfolio remains constant as long as rl_t, θ_{lp}, q_t, and λ remain constant

$$
pvx_{ss} = \frac{(1-q_{ss})(\theta_{lp}+rl_{ss})+\lambda q_{ss}}{1+rl_{ss}-(1-q_{ss})(1-\theta_{lp})}
$$

Time evolution of loan segments with nonzero share of foreign currency denominated loans. We amend the equations presented above for the exchange rate revaluation effects.

Closing balance from previous time $t-1$

$$
lp^k_{t-1}
$$

New time *t:* new information arrives *including the new level of the exchange rate*, we adjust the balance for new information

$$
ln^{\Delta k}_t = j^k_t q_t lp^k_{t-1}
$$

$$
lp^{0k}_t = j^k_t lp^k_{t-1} - ln^{\Delta k}_t
$$

Period cashflows generated by the portfolio: pay-down plus interest income

$$
\big(\theta^k_{lp} + rl^k_{t-1}\big)lp^{0k}_t
$$

Closing balance after pay-down and inclusive of new lending

$$
lp^k_t = \big(1-\theta^k_{lp}\big)lp^{0k}_t + l^{\Delta k}_t
$$

Part B. Delta Method

The delta method is a simple technique to construct a macrofinancial scenario (e.g. a stress scenario or a policy scenario) on top of a baseline scenario. Most commonly, the baseline scenario is obtained by conditioning on a baseline macroeconomic forecast. We then add additional assumptions (unexpected decline of foreign demand, sudden exchange rate depreciation, or rapid worsening of credit performance for idiosyncratic reasons, etc.). After applying the delta method, we obtain the paths of variables in the real and financial sectors that are based on the baseline scenario but deviate consistently with the additional assumptions.

Assume the model can be written in the following form:

$$\begin{bmatrix} X_{m,t} \\ X_{f,t} \end{bmatrix} = A \begin{bmatrix} X_{m,t-1} \\ X_{f,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{m,t} \\ \varepsilon_{f,t} \end{bmatrix} \tag{A.1}$$

where

- X_t is the vector of endogenous variables which comprises of $X_{m,t}$, a vector of macro variables (real GDP, inflation, interest rate, exchange rate, etc.), and $XX_{f,t}$, a vector of financial sector variables
- A is a transition matrix
- $\varepsilon_{m,t}$ and $\varepsilon_{f,t}$ are vectors of exogenous shocks to the macro and financial sector variables, respectively.

This specification does not apply to the MESS model, which is globally nonlinear, but the simplification is productive to explain the crux of the delta method and the explanation easily generalizes to nonlinear models.

In the first step, assume we know the initial condition X_0 and external forecast for macro variables $X^*_{m,t}$ for $t = [1, \dots, T]$. It is trivial to find a sequence of exogenous shocks $\varepsilon^*_{m,t}$ which reproduces macro variables $X^*_{m,t}$. Using these shocks in the equation above, we get

$$\begin{bmatrix} X^*_{m,t} \\ X^*_{f,t} \end{bmatrix} = A \begin{bmatrix} X^*_{m,t-1} \\ X^*_{f,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon^*_{m,t} \\ 0 \end{bmatrix}, \quad t = [1, \cdots, T] \tag{A.2}$$

where $X^*_{f,0} = X_{f,0}$ and $X^*_{m,0} = X_{m,0}$.

Therefore we can recover $X^*_{f,t}$, which represents the paths of financial sector variables consistent with the external forecast for macro variables $X^*_{m,t}$. This is the baseline scenario which is consistent with the external macroeconomic forecast. Note that using the equation above we only need the initial condition X_0, the transition matrix A, and the sequence of shocks $\varepsilon^*_{m,t}$ to reproduce the baseline scenario.

In the second step, we add additional shocks (delta shocks) on top of those from the first step to define a new scenario

$$\begin{bmatrix} \varepsilon^{**}_{m,t} \\ \varepsilon^{**}_{f,t} \end{bmatrix} = \begin{bmatrix} \varepsilon^{*}_{m,t} \\ 0 \end{bmatrix} + \begin{bmatrix} \varepsilon^{\Delta}_{m,t} \\ \varepsilon^{\Delta}_{f,t} \end{bmatrix}$$

Note that these additional shocks can be shocks to the real variables, financial variables, or both. Note that these shocks *do not replace* the baseline scenario shocks but are rather *added* to these shocks. For example, if we add unit sized shock that represent idiosyncratic tightening of bank lending conditions, which is part of vector $\varepsilon_{f,t}$ we get

$$\begin{bmatrix} \varepsilon^{**}_{m,t} \\ \varepsilon^{**}_{f,t} \end{bmatrix} = \begin{bmatrix} \varepsilon^{*}_{m,t} \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ \vdots \\ 1 \end{bmatrix} \tag{A.3}$$

Assume that we want to combine the shock representing idiosyncratic tightening of bank lending conditions with another shock which affects a macro variable. In this case, we might get a new set of shocks that looks like this

$$\begin{bmatrix} \varepsilon^{**}_{m,t} \\ \varepsilon^{**}_{f,t} \end{bmatrix} = \begin{bmatrix} \varepsilon^{*}_{m,t} \\ 0 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 1 \end{bmatrix} \tag{A.4}$$

To calculate the final scenario, we set

$$\begin{bmatrix} X^{**}_{m,t} \\ X^{**}_{f,t} \end{bmatrix} = A \begin{bmatrix} X^{**}_{m,t-1} \\ X^{**}_{f,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon^{**}_{m,t} \\ \varepsilon^{**}_{f,t} \end{bmatrix}, \quad t = [1, \cdots, T] \tag{A.5}$$

where $X^{**}_{f,0} = X_{f,0}$ and $X^{**}_{m,0} = X_{m,0}$.

It is obvious that the new vector of shocks ε^{**}_t contains the baseline scenario shocks ε^{*}_t with additional shocks on top of that. Therefore the resulting scenario X^{**}_t based on shocks ε^{**}_t is built on top of the baseline scenario X^{*}_t, with the difference attributable clearly to the additional shocks.

It is important to note that we generally avoid using maximum likelihood methods such as the Kalman filter to identify the shocks mentioned above. Firstly, employing these methods requires a linear model; however, our model is highly non-linear, making the use of a linearized version inappropriate as it would produce significantly biased results. Secondly, the additional shocks, denoted as ε^{Δ}_t (delta shocks), correspond to a specific scenario generally grounded in a narrative that provides broader context, facilitating the proper interpretation of the scenario. Consequently, it is vital to preserve the narrative aspect of the simulation, which obliges us to select the shocks ourselves, rather than relying on a statistical method to make that determination.

Part C. Guidelines for Model Calibration

MESS falls into the category of model frameworks whose parameters cannot be directly estimated for a number of reasons.

- Typical duration of financial cycles. Available data typically cover at most two financial cycles (usually less) with brief episodes of distress at most. Data generated by “normal” times (when the real economy and the financial system work without stress) fail to provide sufficient information about their interactions under stress.
- Nonlinearities. Estimating nonlinear functions requires large amounts of data.
- Unobserved variables.
- The evolving nature of the financial sector. Reduced-form parameters are not stable over time, but the estimation yields parameter values roughly corresponding to the average of the period.

We briefly describe the following calibration exercises that have proven useful in determining the key parameters:

- Calibrating the steady-state (long-run) characteristics.
- Matching model behavior (simulations) to data.
- Expert judgment.

Calibrating the steady-state (or long-run) characteristics

Assuming sufficient data are available, a fair number of parameters can be calibrated to match the long-run tendencies observed in the data. The parameters can either be assigned directly (e.g., the minimum CAR), or can be reverse engineered (e.g. parameter θ can be calculated so as to fit the ratio of newly issued loans to the stock of loans).

Since the banking sector is modeled in its aggregate, the data used for calibration need to be consolidated for the whole banking sector. If the model features portfolio segmentation, the corresponding parameters apply to the level of loan segments.

Also, the past average patterns observed in the data may not be informative about the future, typically in times of major policy changes (e.g. new prudential regulations being introduced) or long-run structural changes in the economy (e.g. financial innovations). Common sense and best judgment always needs to be applied.

Simulation experiments

A number of simulation experiments can be used to calibrate the parameters that cannot be recovered from the data. If a simulation indicates an unexpected or dubious model behavior, parameters should be changed to remedy that. This calibration method depends on expert understanding of the financial system and should therefore be best conducted with the help of financial stability experts who have a detailed knowledge of bank balance sheets and understanding of relevant historical periods.

Note that each scenario provides insight into calibration of multiple parameters and each parameter should be calibrated based on the full set of scenarios presented below. Nevertheless, additional scenarios can and should be added to the set based on the nature of interesting and relevant historical periods available in the data.

- *Margin hike:* Financial institutions increase their desired return (for various reasons that are not relevant for the simulation), effectively tightening lending conditions. We observe how the tighter lending conditions impact the economy.
- *Increase in default rates*: The loan default rates increase suddenly with a consequent increase in NPLs and decrease in bank profitability. The simulation can be run with the shock as anticipated or unanticipated, providing an insight into how the banking sector reacts to anticipated developments.
- *Standard macroeconomic shocks*: The macroeconomic shocks featuring in standard QPM models.
- *Shock to bank capital:* Sudden drop in the CAR so as to bring the actual CAR near the regulatory limits.
- *Unwarranted optimism or bubble*: simulation where agents expect large increase of income in the future, which fuels credit creation, depresses default rates, and boosts asset prices. The increase of income however fails to materialize and the financial system deleverages with negative consequences for the economy. We observe how the deleveraging process affects the economy.
- *Replicating historical data*: We can attempt to replicate particular periods in the data where the economy exhibited a clear shock and subsequent reaction of the financial sector. An example could be a strong recession or large external shock to credit performance after a large exchange rate depreciation.

Note that the shocks in these simulations should be fairly large to ensure we trigger model nonlinear features.

Expert judgment and scenario-specific parameters

Some parameters (e.g. trend persistence parameters) cannot be recovered from data nor can they be determined from simulations as they do not impact any meaningfully measurable simulation results. These parameters should, instead, be used to define some aspects of particular alternative scenarios (e.g. a faster versus slower convergence of the sustainable long-run trend in the credit-to-GDP ratio to its eventual steady state).

These parameters have to be decided solely based on (i) expert judgment, and (ii) assumptions of the particular experiment in question. This is common practice in scenario-building frameworks, and poses no problem at all as the parameters are not consequential for the whole model performance.

REFERENCES

Aikman D, Haldane AG, Kapadia S (2013): Operationalising a Macroprudential Regime: Goals, Tools and Open Issues. Banco de Espana Estabilidad Financiera, 24.

Benes J, Kumhof M (2012): Chicago Plan Revisited. IMF Working Paper, 12/202.

Benes J, Kumhof M, Laxton D (2014a): Financial Crises in DSGE Models: A Prototype Model. IMF Working Paper, 14/57.

Benes J, Kumhof M, Laxton D (2014b): Financial Crises in DSGE Models: Selected Applications. IMF Working Paper, 14/56.

Benes J, Lees K (2008): Multi-Period Fixed-Rate Loans, Housing and Monetary Policy in Small Open Economies. Reserve Bank of New Zealand Discussion Paper, 2010/03.

Berg A, Karam P, Laxton D (2006): A Practical Model-Based Approach to Monetary Policy Analysis—Overview. IMF Working Paper, 06/80.

Bernanke B, Gertler M, Gilchrist S (1998): The Financial Accelerator in a Quantitative Business Cycle Framework. NBER Working Paper, 6455.

Borio C (2013): On time, stocks and flows: Understanding the Global Macroeconomic Challenges. *National Institute Economic Review*, 225.

Brzoza-Brzezina M, Gelain P, Kolasa M (2014): Monetary and Macroprudential Policy with Multi-Period Loans. Norges Bank Research Paper, 16/2014.

Budnik K, Balatti M, Dimitrov I, Gross J, Kleemann M, Reichenbachas T, Sanna F, Sarychev A, Sinenko N, Volk M (2020): Banking Euro Area Stress Test Model. European Central Bank Working Paper, 2469.

Burrows O, Learmonth D, McKeown J (2012): RAMSI: A Top-Down Stress-Testing Model. Bank of England Financial Stability Paper, 17.

CBI (2022): The Central Bank's Framework for Macroprudential Capital. Central Bank of Ireland, June 2022. https://www.centralbank.ie/docs/default-source/financial-system/ financial-stability/macroprudential-policy/f ramework-for-macroprudential- capital. pdf.

de Bondt G, Maddaloni A, Peydro J-L, Scopel S (2010): The Euro Area Bank Lending Survey Matters: Empirical Evidence for Credit and Output Growth. European Central Bank Working Paper, 1160.

Drehmann M (2013): Total Credit as an Early Warning Indicator for Systemic Banking Crises. *BIS Quarterly Review*, June 2013.

Drehmann M, Sorensen S, Stringa M (2010): The Integrated Impact of Credit and Interest Rate Risk on Banks: A Dynamic Framework and Stress Testing Application. *Journal of Banking and Finance*, 34(2010).

Duffie D, Singleton KJ (1999): Modeling Term Structures of Defaultable Bonds. *The Review of Financial Studies,* 19(4).

Engelmann B (2020): Calculating Lifetime Expected Loss for ifrs 9: Which Formula Is Measuring What? *Journal of Risk Finance*, 22(3/4).

ESRB (2019): Expected Credit Loss Approaches in Europe and the United States: Differences From A Financial Stability Perspective. European Systemic Risk Board, January 2019, https://www.esrb.europa.eu/pub/pdf/reports/esrb.report190116_expectedcreditlossapproachesEuropeUS.en.pdf.

Estrella A (2004): The Cyclical Behavior of Optimal Bank Capital. *Journal of Banking and Finance*, 28(2004).

Fique J (2017): The MacroFinancial Risk Assessment Framework (MFRAF), Version 2.0. Bank of Canada Technical Report, 111.

Galati G, Moessner R (2011): Macroprudential Policy - A Literature Review. BIS Working Paper, 337.

Garcia Revelo JD, Levieuge G (2022): When Could Macroprudential and Monetary Policies be in Conflict? *Journal of Banking and Finance*, 139(2022).

Gupta RD, Kundu D (2010): Generalized Logistic Distributions. *Journal of Applied Statistical Science*, 18(1).

Haldane AG (2014): Ambidexterity. Speech delivered at the American Economic Association Annual Meeting, Philadelphia on 3 January 2014.

Hlawatsch S, Ostrowski S (2010): Economic Loan Loss Provision and Expected Loss. *Business Research*, 3(2).

Markovic B (2006): Bank Capital Channels in the Monetary Transmission Mechanism. Bank of England Working Paper, 313.

Milne A (2010): *Macro-Prudential Policy: An Assessment.* CESifo DICE Report, Institut fur Wirtschaftsforschung an der Universitat Miinchen, Miinchen*, 08(1).*

Peura S, Keppo J (2006): Optimal Bank Capital with Costly Recapitalization. *Journal of Business*, 79(4).

Strahan PE (1999): Borrower Risk and the Price and Nonprice Terms of Bank Loans. Federal Reserve Bank of New York Staff Report, 90.

Van den Heuvel SJ (2008): The Welfare Cost of Bank Capital Requirements. *Journal of Monetary Economics*, 55(2008).

Werner R (2012): Towards a New Research Programme on Banking and the Economy — Implications of the Quantity Theory of Credit for the Prevention and Resolution of Banking and Debt Crises. *International Review of Financial Analysis*, 25(2012).

Zhang L (2009): Bank Capital Regulation, the Lending Channel and Business Cycles. Deutche Bundesbank Discussion Paper, 33/2009.